LEARNING AUTOMATA AND SIGMA IMPERIALIST COMPETITIVE ALGORITHM FOR OPTIMIZATION OF SINGLE AND MULTI OBJECTIVE FUNCTIONS

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To my beloved mother, father and wife

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ABSTRACT

Evolutionary Algorithms (EA) consist of several heuristics which are able to solve optimisation tasks by imitating some aspects of natural evolution. Two widely-used EAs, namely Harmony Search (HS) and Imperialist Competitive Algorithm (ICA), are considered for improving single objective EA and Multi Objective EA (MOEA), respectively. HS is popular because of its speed and ICA has the ability for escaping local optima, which is an important criterion for a MOEA. In contrast, both algorithms have suffered some shortages. The HS algorithm could be trapped in local optima if its parameters are not tuned properly. This shortage causes low convergence rate and high computational time. In ICA, there is big obstacle that impedes ICA from becoming MOEA. ICA cannot be matched with crowded distance method which produces qualitative value for MOEAs, while ICA needs quantitative value to determine power of each solution. This research proposes a learnable EA, named learning automata harmony search (LAHS). The EA employs a learning automata (LA) based approach to ensure that HS parameters are learnable. This research also proposes a new MOEA based on ICA and Sigma method, named Sigma Imperialist Competitive Algorithm (SICA). Sigma method provides a mechanism to measure the solutions power based on their quantity value. The proposed LAHS and SICA algorithms are tested on well-known single objective and multi objective benchmark, respectively. Both LAHS and MOICA show improvements in convergence rate and computational time in comparison to the well-known single EAs and MOEAs.

ABSTRAK

Algoritma Berevolusi (EA) terdiri daripada beberapa heuristik yang boleh menyelesaikan tugas-tugas pengoptimuman dengan meniru beberapa aspek evolusi semula jadi. Dua EA yang digunakan secara meluas, iaitu Carian Harmoni (HS) dan Algoritma Persaingan Imperialis (ICA) telah dipertimbangkan masing-masing untuk mempertingkatkan objektif tunggal EA dan Objektif Pelbagai EA (MOEA). HS popular kerana kelajuannya dan ICA mempunyai keupayaan untuk meloloskan dari optima tempatan, yang merupakan satu kriteria penting bagi MOEA. Walau bagaimanapun, kedua-dua algoritma tersebut telah mengalami beberapa kekurangan. Algoritma HS mungkin terperangkap di optima tempatan jika parameternya tidak ditala dengan betul. Kekurangan ini menyebabkan kadar penumpuan yang rendah dan masa pengiraan yang tinggi. Dalam ICA, terdapat halangan besar yang menghalang ICA daripada menjadi MOEA. ICA tidak boleh dipadankan dengan kaedah jarak sesak yang menghasilkan nilai kualitatif untuk MOEA, manakala ICA memerlukan nilai kuantitatif untuk menentukan kuasa setiap penyelesaian. Kajian ini mencadangkan satu EA boleh belajar, yang dinamakan pembelajaran carian harmoni automata (LAHS). EA menggunakan pendekatan berasaskan automata pembelajaran (LA) untuk memastikan parameter HS ini boleh dipelajari. Kajian ini juga mencadangkan satu MOEA baru berdasarkan kepada ICA dan kaedah Sigma, yang dinamakan Algoritma Persaingan Imperialis Sigma (SICA). Kaedah Sigma menyediakan satu mekanisme untuk mengukur kuasa penyelesaian berdasarkan nilai kuantiti mereka. Algoritma LAHS dan SICA yang dicadangkan masing-masing diuji penanda aras pada objektif tunggal dan berbilang objektif yang terkenal. Kedua-dua LAHS dan SICA menunjukkan peningkatan dalam kadar penumpuan dan masa pengiraan berbanding dengan EA tunggal dan MOEA yang terkenal.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATION

BW	-	Band Width
CCP	-	Coverage Configuration Protocol
EA	-	Evolutionary Algorithm
ECCA	-	Energy-Efficient Coverage Control Algorithm
GA	-	Genetic Algorithm
GAF	-	Geographical Adaptive Fidelity
GHS	-	Global Harmony Search
GSO	-	Glowworm Optimization Algorithm
HM	-	Harmony Memory
HMCR	-	Harmony Memory Consideration Rate
HMS	-	Harmony Memory SIZE
HS	-	Harmony Search
ICA	-	Imperialist Competitive Algorithm
IHS		Improved Harmony Search
LA	-	Learning Automata
LAHS	-	Learning Automata Harmony Search
MOEA	-	Multi Objective Evolutionary Algorithm
SICA	-	Sigma Imperialist Competitive Algorithm
NSGA	-	Non-Dominated Genetic algorithm
NSGA-II	-	Fast Non-dominated sorting genetic algorithm
OGDC	-	Optimal Geographical Density Control
PAR	-	Pitch Adjustment Rate
PSO	-	Particle Swarm Optimization
SGHS	-	Self-adaptive Global-best Harmony Search
SD	-	Standard Deviation
WSN	-	Wireless Sensor Network

CHAPTER 1

INTRODUCTION

1.1 Overview

Optimization is the process of seeking values of the variables that lead to an optimal value of the function that is to be optimized. Generally, when optimization is applied to a problem, it is desired to adjust the problem variables in order of finding the 'best' configuration. A variety of engineering problems are categorized in optimization domain. Therefore, finding efficient, robust and practical methods for solving these methods has been of wide interest among researchers and engineers. Exhaustive search seems to be the simplest way of optimum finding where all possible solutions are tested to find the best one. On the contrary to its simplicity, this method is not practical due to its huge computational time that sometimes makes it even impossible. With the advent of genetic algorithms (GAs) in the late 1980's (Goldberg *et al.*, 1989), these methods have been successfully tried on optimization problems and proved to be efficient. Ever since, the evolutionary computation concept has been an active field of research and many studies have been attempted to develop new algorithms for improving accuracy, efficiency and computational time of the existing ones. The introduced Evolutionary Algorithms (EAs) are based on a natural process, for example swarm intelligence in Particle Swarm Optimization (PSO) (Kennedy *et al.*, 1995) and Glow Worm Optimization (Krishnanand and Ghose, 2009), social-political evolution of countries in Imperialist Competitive Algorithm (ICA) (Atashpaz-Gargari and Lucas, 2007) and musical improvisation in Harmony Search (HS) algorithm (Geem *et al.*, 2001). One of the significant problems in using these types of algorithms is their high dependency on their parameters.

Fine tuning of the algorithm parameters could greatly affect the output results. Therefore, one of the main concerns of this thesis is to present a learning based approach to eliminate the parameter setting and enhance the performance of EAs. Learning automata introduced by Tsetlin (1973) is implemented in the evolution process of the EAs and controls the parameters based on its previous experience. The learning approach has been proved to significantly improve the success rate of particle swarm optimization in the previous studies (Hashemi and Meybodi, 2011).

Most of the previous studies have been focused on single objective optimization while the majority of the real world optimization problems contain two or more conflicting objectives that should be considered simultaneously. It is a complicated task since usually no prior information of their exact interactions is available. For instance, in any product design, achieving a minimum production cost is often receives a great interest whilst a corporation may wish to achieve the highest possible quality as well. Obviously, these objectives could not be satisfied by a single solution. Therefore, considering a given set of constraints (for example, size limits of the product, legal requirements, and production time) different combination of these objectives could be achieved by adjusting the design variables.

A curve (for two objectives) or surface (for more than two objectives) that includes solutions representing all optimal trade-off possibilities of the objectives is called Pareto front. Considering any solutions lying on Pareto front, no feasible solutions exists in the search space that improves one or more objectives without degrading at least one of the others simultaneously. Hence, any multi-objective algorithm should aim at tracing the Pareto front of these non-dominated solutions.

Multi-objective evolutionary algorithms (MOEAs) utilize evolutionary search techniques to deal with these problems. The evolutionary algorithms (EA) are suitable in Multi Objective Problems (MOPs) since a large number of variables and objectives are usually involved which make the optimization task significantly complex. Moreover, EAs are population based and could explore various parts of the Pareto front at the same time. GA have been utilized in many MOEAs including MOGA (Hakimi-Asiabar *et al.*, 2009; Ko and Wang, 2011), non-dominated sorting genetic algorithm (NSGA) (Guria *et al.*, 2005), fast elitist non-dominated sorting genetic algorithm (NSGA-II) (Deb *et al.*, 2002; Jia *et al.*, 2009; Ramesh *et al.*, 2012) and etc. Numerical results from various studies have indicated that NSGA-II outperforms other GA based MOEAs (Deb *et al.*, 2002). Owing to the promising results presented by Particle Swarm Optimization (PSO) in single objective optimization problems (Altinoz and Yilmaz, 2012; Poli *et al.*, 2007), various studies have tried to make use of swarm intelligence for developing MOEAs (Chen *et al.*, 2011; Liu *et al.*, 2007; Sundar and Singh, 2012). Utilizing PSO and fast non-dominated sorting, developed MOPSO (Coello Coello and Lechunga, 2000) that has proved its efficiency ever since (Ali *et al.*,2012; Hu *et al.*, 2011; Moslemi and Zandieh, 2011).

Hence, one of the primary concerns of this study is to develop a MOEA based on the newly introduced EAs to utilize their capabilities in the multi-objective domain. The new method uses fast non-dominated sorting and Sigma method for ranking. To demonstrate the performance of Sigma Imperialist Competitive Algorithm (SICA), it has been applied on various well-studied benchmark problem. The numerical results are compared with those obtained by NSGA-II and MOPSO.

1.2 Background of the Study

After the introduction of GA and its enormous success in optimization domain, researchers have been trying to develop more efficient EAs in terms of accuracy, efficiency and computational time. PSO was introduced in 1995 inspired by a flock of birds in search for food. Due to its simplicity and great performance, it became popular among researchers and engineers rapidly. However, PSO has its own particular drawback: its dependency on the proper selection of its parameters. PSO could easily get trapped in local optima if the parameters are not selected properly.

Ever since, many studies have been focusing on improving particle swarm optimization. These attempts could be classified as.

1. Parameters adjusting in standard particle swarm optimization (Chatterjee and Siarry, 2006; Clerc and Kennedy, 2002; Shi and Eberhart, 1998).
2. Designing different population topologies (Hu and Eberhart, 2002; Kennedy, 1999; Kennedy and Mendes, 2002; Suganthan, 1999).
3. Combining particle swarm optimization with other search techniques (Juang, 2004; Zhang and Xie, 2003).
4. Incorporating bio-inspired mechanisms into the basic particle swarm optimization (He *et al.*, 2004; Løvbjerg *et al.*, 2001; Xie *et al.*, 2002).

5. Utilizing multi-population scheme instead of single population of the basic particle swarm optimization (Niu *et al.*, 2005a; Niu *et al.*, 2005b; van den Bergh and Engelbrecht, 2004).

Despite the improvement these methods have brought to the original PSO, they have introduced new parameters in the algorithm that consequently increase the complexity of the model. Recently, Hashemi and Meybodi (2011), applied learning automata for parameters selecting. The proposed method does not add any new parameter, yet improves the performance of PSO.

Learning automata, which have been employed successfully in many engineering applications, operate in an unknown stochastic environment and adaptively improve their performance through a learning process. Some of the applications of LA are: call admission control in cellular networks (Beigy and Meybodi, 2002, 2005), capacity assignment problems (Oommen *et al.*, 2000), adaptation of back propagation parameter (Meybodi and Beigy, 2002), and determination of the number of hidden units for three layers neural networks (Beigy and Meybodi, 2009).

HS algorithm was developed by Geem, inspired by the improvisation process of musicians (Geem *et al.*, 2001). It has gained much attention in recent years because (a) it has fewer mathematical parameters compared to other meta-heuristics and (b) it is adaptable to a wide range of applications given that it can deal with both continuous and discrete variables without additional effort. Recently, the HS algorithm has been effectively used in a wide range of engineering applications (Cao and Wang, 2012; Geem, 2006; Geem, 2007; Pan *et al.*, 2011; Saka, 2009; Santos Coelho and de Andrade Bernert, 2009; Vasebi *et al.*, 2007). Nevertheless, similar to PSO, it has a serious drawback that is its sensitivity to the fine-tuning of its parameters. Therefore, different studies were focused on HS parameter setting. However, these methods were basically tested on low-dimensional problems and were not rigorous enough in high-dimensional ones.

Musical improvisation is a creative activity of immediate musical composition where performance should be combined with emotions as well as spontaneous responses. To enable spur-in-time responses, a learning automaton process should be implemented to immediately tune the HS parameters regarding to the harmony feedback employed in this variant of the HS. This learning-based adjustment mechanism not only solves the difficulties of parameter setting, but also enhances the local search abilities of the algorithm.

Imperialist competitive algorithm (ICA) was proposed in 2007 inspired by social-political evolution of countries in an imperialistic competition. This evolutionary optimization algorithm has been successfully utilized in many engineering applications such as control (Lucas *et al.*, 2010), data clustering (Niknam *et al.*, 2011), industrial engineering (Nazari-Shirkouhi *et al.*, 2010) in recent years and has shown great performance in both convergence rate and achieving global optima. However, ICA performance could be further improved in MOPs cases.

Owing to the promising results obtained by swarm intelligence based PSO, glowworm optimization algorithm (GSO) was proposed on the same basis (Krishnanand and Ghose, 2005). The behavior of ants, honeybee swarms, flocking of birds and fish schools demonstrate that even complicated goals could be achieved by simple interactions of individuals. In a swarm, the decision are not taken individually, hence it is suitable in multi-agent algorithms. GSO was inspired by the behavior of Glowworms which are a type of insects that have the ability to modify their light emission and use the bioluminescence glow for different purposes. In GSO, agents locally interact to exchange information. In addition, their movements are not deterministic.

Although, most of the real-world optimization problems are multi-objective, it has not gained due attention comparing to single-objective ones. The application of EAs in MOPs was first presented in 1985 by Schaffer (1985) and these EAs were called multi-objective evolutionary algorithms (MOEAs). However, the first notable EA developed in this domain was the Non-dominated Genetic algorithm (NSGA). The main disadvantageous of NSGA were reported over the years as follow.

1- High computational complexity of non-dominated sorting

2- Lack of elitism

3- Need for specifying the sharing parameter σ_{share}

As a result an improved version called fast non-dominated sorting genetic algorithm (NSGA-II) was proposed (Deb *et al.*, 2002). The new algorithm has responded all the above-mentioned criticisms. Ever since, NSGA-II has been the main framework for most of the MOEAs where a selection operator based on Pareto domination and a reproduction operator are used iteratively. Among other successful EAs, PSO have been developed for MOPs. To develop a multi-objective PSO, MOPSO, there were two issues to be taken into account. First is how to find the best global and local best particles and the second is how to maintain the good points during the course of evolution. The latter is achieved by usually creating a secondary population to keep the good individuals. For the former, different methods were employed that could be shown in Table 1.1.

Table 1.1: Various used methods for improving the optimization algorithms

Authors	Methods
Janson, Merkle et al. 2008	Clustering the particles into groups and find the global best within each group by applying the weighted sum of all objectives
Liu, Tan et al. 2008	Selecting the global best particle by tournament niche method and updating the local best by Pareto dominance
Tripathi, Bandyopadhyay et al. 2007	Selecting the best particle from the non-dominated solutions using a roulette wheel selection where the density values are defined as fitness
Wang, Wong et al. 2009	Ranking all the particles by a simplification of Pareto dominance called preference order to identify the global best particle
Rahimi-Vahed, Mirghorbani et al. 2007	Selecting the global best from the non-dominated solution in the archive with highest crowded distance

Other well-known EAs namely ICA algorithm and GSO have not been employed in multi-objective optimization domain.

1.3 Problem Statement

Optimization is the process of finding one or more solutions of a problem for achieving extreme values of one or more objectives. In artificial intelligence, an evolutionary algorithm is a subset of evolutionary computation, a generic population-based heuristic optimization algorithm. It has been an active field of research as the real world optimization problems have become progressively more complex in recent years. There are two types of optimization problems that should be considered. First, single objective, is a type of optimization problem that focus on problems including one objective or numbers of objectives with the same direction. Second category is multi objective problems (MOPs) which have at least two conflicting objectives. Many new evolutionary based algorithms have been proposed to tackle this problem based on various evolution phenomena (Deb *et al*., 2002; Coello Coello and Lechunga., 2000). The new EAs have been tested on different benchmark problems and employed in real-world engineering problems. The results have indicated their advantageous over the conventional optimization algorithms. However, the capabilities of these new EAs in terms of convergence rate and computational time could be further improved.

One of the well-design EA is HS algorithm where used to solve single objective optimization problem (Geem *et al.*, 2001). One of the common drawbacks of the HS is that there always exists a possibility that the algorithm converges to a local optima solution instead of the global optima point (Mahdavi *et al.*, 2007). The local-optima trap could deter the algorithm from finding the desired solutions especially in the problems that too many local optima solutions exist. The efficiency of an HS depends greatly on its ability to escape these so-called local traps and converge to the desired solution that mostly depends on the proper selection of the EAs parameters. The parameter setting of an HS is a cumbersome process and has to be repeated for any new problem, as the parameter setting is problem dependent. Implementing learning capabilities for parameter setting of the HS can help them adjust their parameters automatically considering the feedback they receive in the course of optimization. This enhancement not only eliminates the time-consuming parameter setting of the HS, but also further improves the efficiency of the algorithm in terms of convergence rate.

On the other hand, most of the real world problems are categorized as multi-objective problems where two or more conflicting objectives should be considered simultaneously. When an MOP is solved by traditional mathematical techniques, only a single solution is presented in a single run that makes the approach unsuitable for solving MOPs. On the contrary to the former, evolutionary computation paradigm can generate a set of solutions in a single run and hence be suitable in this field. Various multi-objective evolutionary algorithms have been successfully developed for solving MOPs. However, more efficient algorithms are still needed to be developed to overcome the drawback of the existing approaches in terms of computational time and convergence rate. The advantageous of the newly introduced single-objective EAs in terms of convergence rate and computational time could be used in the multi-objective optimization area by developing multi-objective evolutionary algorithm (MOEAs) based on them. Another deficiency in current MOEAs is their disability to determine the quantitatively merit of each solution. Crowded distance which is used as the ranking method in MOEAs (Deb *et al*., 2002; Coello Coello and Lechunga., 2000), is just able to evaluate solution, quantitatively. This weakness causes many single objective evolutionary algorithms abdicate to become MOEA. Therefor the lack of method for measuring the quantitatively merit of solution is felt.

The proposed algorithms are usually tested on the well-known benchmark problems. Although the benchmark problems are carefully designed and selected to incorporate different aspects and challenges of any optimization problem, real-world optimization problems can better examine the efficiency and applicability of a newly introduced algorithm.

Hence, the research questions of this study can be stated as.

1- How learning capability could improve the convergence rate and computational time of the existing evolutionary algorithms?
2- How new ranking method could propose to measure the quantitatively merit of each solution?
3- How more efficient multi-objective algorithms could be developed for tackling MOPs?

1.4 Research Goal

The main goal of this study is to improve the evolutionary algorithms both in single and multi-objective optimization. It is desired to make the HS in single-objective optimization more efficient and powerful by improving their convergence rate and time complexity. This goal will be satisfied when the HS algorithm equipped by LA. The LA tool can be applicable to tune HS parameters in order to avoid local optima, increase converge rate and decrease computational time. Moreover, the study aims at developing more efficient and robust MOEA by making use of new ranking method that is employed for measuring quantitatively merit of each solution. This new ranking method potentially makes single objective imperialist competitive algorithm to become very powerful and useful MOEA.

1.5 Research Objective

The main objectives of the study are as following.

1- To propose a new single objective evolutionary algorithm, namely learning automata harmony search (LAHS), which is able to improve harmony search performance in terms of convergence rate and computational time.

2- To propose new quantitatively ranking method namely Sigma method

3- To develop new multi-objective evolutionary algorithms based on the Sigma method, namely Sigma Imperialist Competitive Algorithm (SICA).

1.6 Research Scope

1. This research is focused on evolutionary computation field. Other mathematical optimization tools are not to be explored.
2. Only the well-established and well-known EAs being applied in different engineering applications are to be explored.
3. MATLAB is used for programming.
4. The algorithms are to be tested on a set of well-established benchmark problems and a limited number of engineering applications

1.7 Significant of Study

This research improves the convergence rate and computational time in both single objective and multi objective evolutionary algorithm. This study is applicable for scientists who want to solve real engineering problem in both single objective and multi objective problem. The results of this research assist scientists to have a single objective and multi objective evolutionary algorithm by reasonable convergence rate and computational time.

The outcome of this research can be used in industry and laboratories for solving real engineering problems, which can increase the performance of existing methods and decreasing the costs.

1.8 Thesis Organization

The rest of the thesis is organized as follows. A comprehensive exploration on the existing literature in the evolutionary algorithm is presented in Chapter 2. In this chapter, advantages and disadvantages of the existing HS algorithms and MOEAs algorithms are explained in details. Common steps to reach to proposed methods and normal criteria for evaluating the proposed methods are presented in Chapter 3. Chapter 4 is dedicated to explain the Learning Automata Harmony Search (LAHS) method and its relevant experiments. In this chapter first LAHS performance is measured when standard single objective function is considered as the test function and then LAHS ability to solve real engineering problem, electrical load forecasting, is tested. Chapter 5 introduces second proposed method, namely Sigma Imperialist Competitive Algorithm (SICA), then discusses the numerical results on various multi objective benchmark problems and coverage problem in wireless sensor network (WSN). Finally, the conclusion and future work of thesis is drawn in Chapter 6.

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BAHAGIAN A : Pengesahan Kerjasama*

Adalah disahkan bahawa projek penyelidikan tesis ini telah dilaksanakan melalui kerjasama antara ______________________ dengan ______________________

Disahkan oleh:

Tandatangan :	....	Tarikh :	....
Nama :	....		
Jawatan :	....		
(Cop Rasmi) :			

**Jika penyediaan tesis/projek melibatkan kerjasama.*

BAHAGIAN B : Untuk Kegunaan Pejabat Sekolah Pengajian Siswazah

Tesis ini telah diperiksa dan diakui oleh:

Nama dan Alamat Pemeriksa Luar : ______________________________

____

____

Nama dan Alamat Pemeriksa Dalam : ______________________________

____

____

Nama Penyelia Lain (jika ada) : ______________________________

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Disahkan oleh Penolong Pendaftar di SPS:

Tandatangan:	....	Tarikh :	....
Nama :	....		